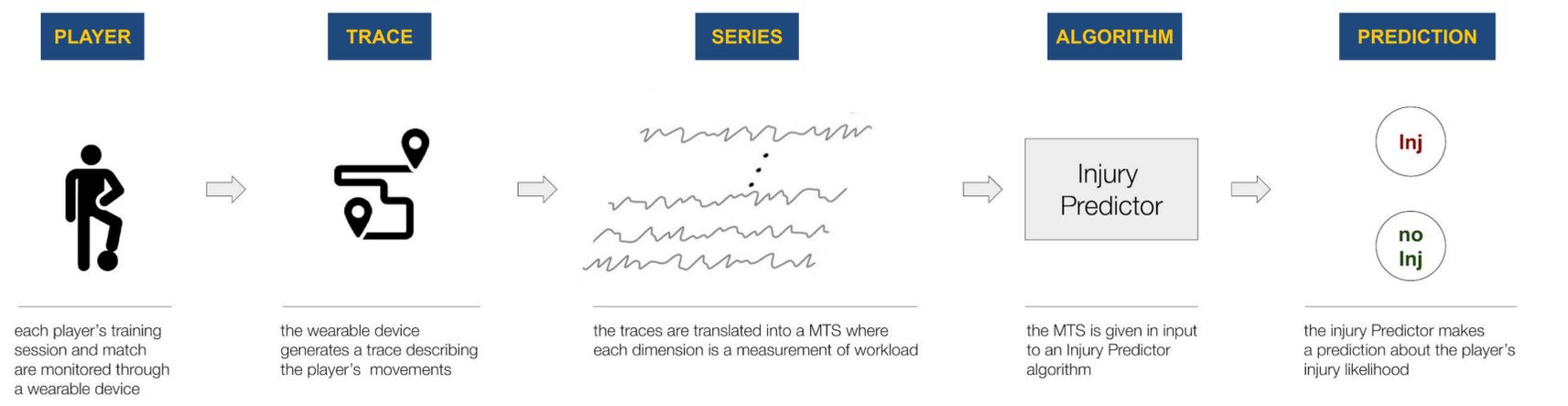


Explainable Injury Forecasting via Multivariate Time Series and Convolutional Neural Networks

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GOAL TO TRAIN AN INJURY FORECASTER BASED ON GPS TRAINING FEATURES



Decision Tree

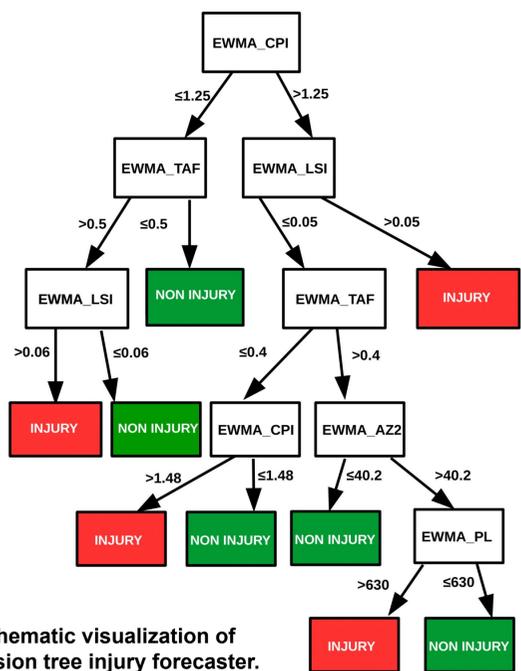
Convolutional Neural Network

EXPLAINABLE ✓

EXPLAINABLE ✓

No need for FEATURE ENGINEERING ✗

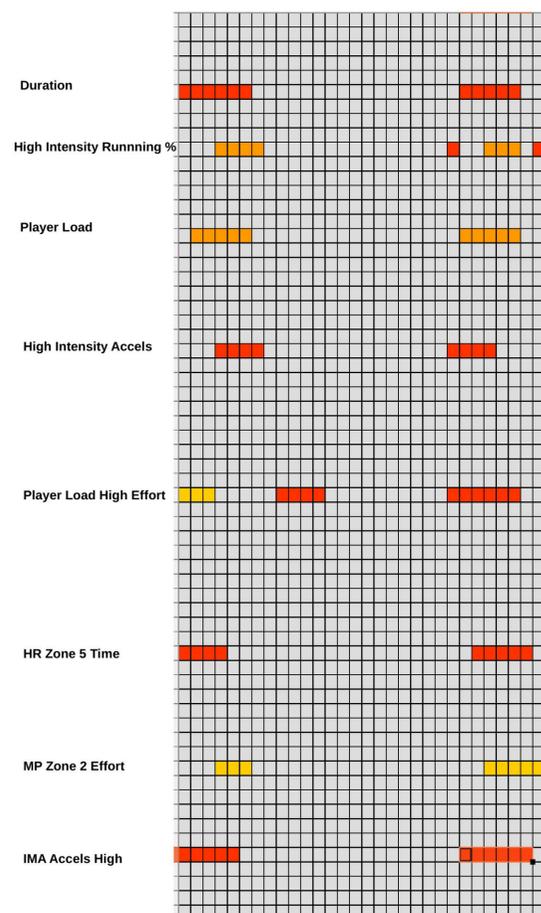
No need for FEATURE ENGINEERING ✓



A schematic visualization of decision tree injury forecaster. White boxes are decision nodes, green boxes are leaf nodes for class No-Injury, red boxes are leaf nodes for class Injury.

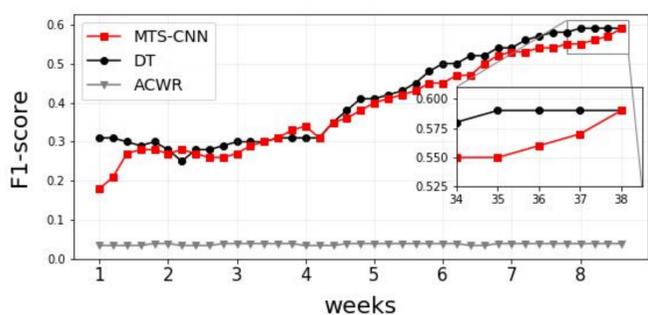
PRECISION 50% (4%)
RECALL 80% (43%)

CPI = Previous Injury Count; TFA = Training After Injury; LSI = Injury time series; AZ2 = acceleration above 2m/s²; PL = Player Load.



Explanation of a correctly classified injury workload history. Rows represent workload features and columns training sessions. Colors are assigned according to how much relevant is a cell to the CNN's decision making (grey no-relevant; yellow not very relevant up to red very relevant).

PRECISION 48% (4%)
RECALL 72% (43%)



Evolution of the cumulative F1-score of the CNN, DT and ACWR. The inset zooms on the last part of the season.